EDGE SENSING FOR HIGH QUALITY IMAGE USING DEMOSAICKING

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Abstract -The need for image demosaicking arises from the Color subsampling process that occurs when Color image is acquired by a single sensor digital camera through a color filter array. Digital cameras that use Color Filter Arrays (CFA) entail a demosaicking procedure to form full RGB images. To digital camera industry, demosaicking speed is as important as demosaicking accuracy. Moreover, the cost associated with demosaicking should not go beyond the cost saved by using CFA.In this project, propose a very low cost edge sensing, which guides demosaicking by a logistic functional. It estimates the difference between directional variations. LED achieves the accuracy higher than many recently proposed methods on low resolution images. Objective is Propose a high-quality fast edge-sensing image demosaicking scheme that adopts the HA work-flow to achieve instant image visualization in high resolution digital cameras.

***Key Words*:**color filter array, edge sensing, subsampling, logistic function

1.INTRODUCTION

Digital color images in an acquisition system are generally described by arrays representing the three color components of each pixel. In this paper a very low cost edge sensing strategy, termed as LED, for color image demosaicking. It guides the green channel interpolation and color difference plane interpolation by logistic functional of the difference between directional variation. This approach is to derive a logistic functional to blend the diagonal and anti-diagonal estimation, leveraging the diagonal symmetry of the Bayer pattern. Then the green channel interpolation scheme is applicable to computing the rest missing values in the green-red and green-blue difference planes. The proposed demosaicking process is highly parallelizable: although the red and blue channels have to be estimated subsequently to the green channel estimation, the restoration in each step at a pixel is independent of the restoration of other pixels.

The paper [1] introduces a nonlinear interpolation scheme based on edge information that produces high-quality visual results. The new method is especially good at reconstructing the image around edges, a place where the visual human system is most sensitive. [2] gives a new insights for the representation of single-color per spatial location images and enables formal and controllable procedures to design demosaicing algorithms that perform well compared to concurrent approaches, as demonstrated by experiments. An efficient filter for estimating the luminance at green pixels of the CFA image and devise an adaptive filtering approach to estimating the luminance at red and blue pixels is shown in [3]. Experimental results on simulated CFA images, as well as raw CFA data, verify that the proposed method outperforms the existing state-of-the-art methods both visually and in terms of peak signal-to-noise ratio, at a notably lower computational cost. Paper [11] presents a new colordemosaicking technique of optimal directional filtering of the green-red and green-blue difference signals. Under the assumption that the primary difference signals (PDS) between the green and red/blue channels are low pass, the missing green samples are adaptively estimated in both horizontal and vertical directions by the linear minimum mean square-error estimation (LMMSE) technique. These directional estimates are then optimally fused to further improve the green estimates. Finally, guided by the demosaicked full-resolution green channel, the other two color channels are reconstructed from the LMMSE filtered and fused PDS. The experimental results show that the presented colordemosaicking technique outperforms the existing methods both in PSNR measure and visual perception.

2. METHODOLOGY:

2.1 Mosaicking Image:

Single color imaging using CFA is widely used in the current digital camera industry.In single-sensor camera with the CFA, only one pixel value among RGB values is recorded at each pixel. The color configurations is the Bayer CFA, which consists of 50% of green color & 25% of red and blue color. Interpolate the missing G pixel values first, because the G pixels have a double sampling density of R and B pixels.

2.2 Green channel demosaicking:

HA algorithm first computes its horizontal and vertical intensity variation, then selects the less variation direction to perform interpolation. Compute the horizontal and vertical, first and second order partial derivatives. Average of the neighboring green values is then computed in the horizontal and vertical directions. Compute weight of horizontal should be a continuous function, which smoothly blends the estimation from both directions. The green channel is recovered first based on available samples.

2.3 Red and Blue Channels Demosaicking:

Here transform r(Rc) and b(Bc) estimation to (g− r)(Rc) and (g − b)(Bc) interpolation. To respect edges and textures, apply edge-sensing strategy to the red channel. First derive the edge-sensing interpolation scheme for (g-r) using its diagonal and anti-diagonal neighbours.This makes the green red difference values available at the horizontal and vertical neighbours for each of the rest pixels. Then infer r(G) from (g − r)(R) and the estimated (g − r)(B).

2.4 Red and Blue Channels Demosaicking:

Estimating red values at B

The nearest available red values around a pixel located in the diagonal and anti-diagonal directions. To obtain edge

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information, compute the difference between the diagonal and anti-diagonal intensity variation Here, then use the logistic function value of this difference to weight the contribution

Estimating red values at G

Once (g − r)(B) is available, (g − r)(G) can be estimated from its horizontal and vertical neighbours.Note that in this step, for each (i, j) ∈ G, (g − r) values have been already computed at the four nearest neighbours . Compute its horizontal and vertical average values for simply restore the missing colour components by nearest neighbour interpolation.

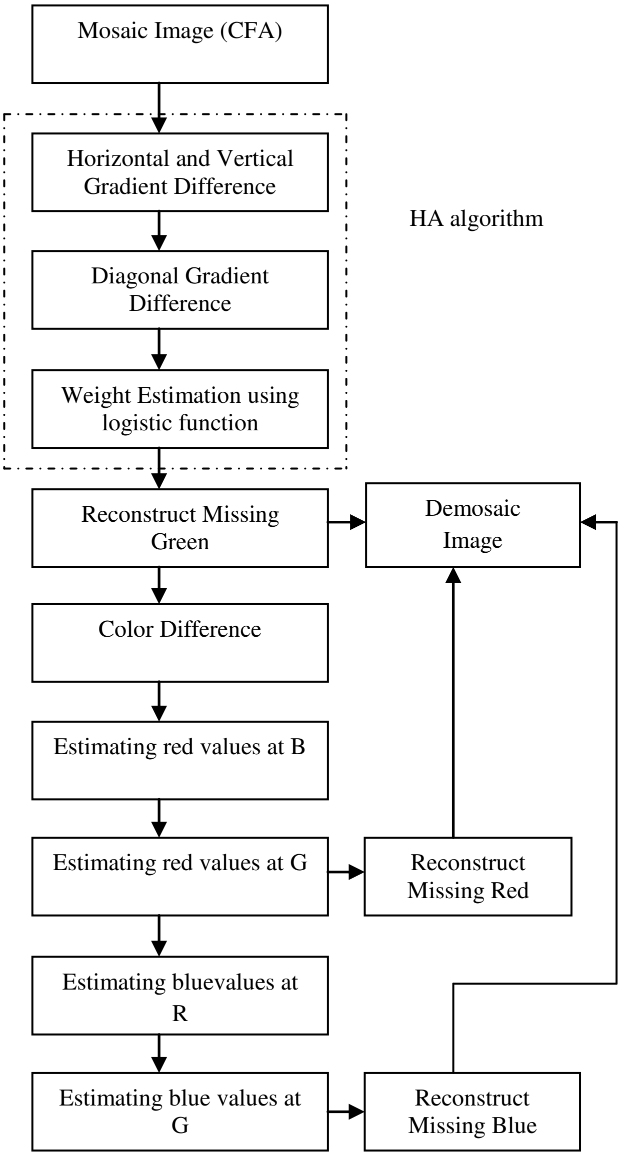

Fig -1: System Architecture

Image simulates the output from a Bayer filtered image sensor; each pixel has red, green or blue component. Twice as many green filters as red or blue ones, catering to the human eye's higher sensitivity to green light. Interpolate the missing G pixel values first, because the G pixels have a double sampling density of R and B pixels.

The HA algorithm first computes its horizontal and vertical intensity variation, then selects the less variation direction to perform interpolation. Weight of horizontal defined by is more flexible than by the value of T has to be carefully defined for each image, as a small bias in T may lead to an opposite interpolation decision. Desirably, weight of horizontal should be a continuous function, which smoothly blends the estimation from both directions, thus a small bias does not cause the demosaicking result to vary abruptly. The green channel is recovered first based on available samples. It is then used to regulate the recovery of the red and blue 240 channels

3. RESULT

Mosaic Image simulates the output from a Bayer filtered image sensor; each pixel has red, green or blue component. Twice as many green filters as red or blue ones, catering to the human eye's higher sensitivity to green light. Interpolate the missing G pixel values first, because the G pixels have a double sampling density of R and B pixels.

Fig-2:Mosaic Image

Hamilton-Adams (HA) algorithm first computes its horizontal and vertical intensity variation, then selects the less variation direction to perform interpolation. Weight of horizontal defined by is more flexible than by the value of T has to be carefully defined for each image, as a small bias in T may lead to an opposite interpolation decision. Desirably, weight of horizontal should be a continuous function, which smoothly blends the estimation from both directions, thus a small bias does not cause the demosaicking result to vary abruptly.

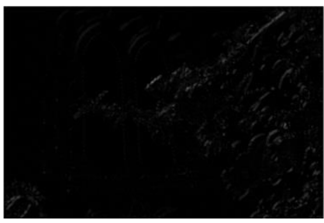


Fig-3:Horizontal &Vertical Gradient **Fig-4:Diagonal Gradient**

The nearest available red values around a pixel located in the diagonal and anti-diagonal directions. To obtain edge information, compute the difference between the diagonal and anti-diagonal intensity variation (in the mosaicked imageplane M). Here, then use the logistic function value of this difference to weight the contribution.


Fig-5:Interpolated missing Red in Green location

Fig-6:Interpolated missing Blue in Green location

The green channel is recovered first based on available samples. It is then used to regulate the recovery of the red and blue 240 channels


Fig-7:Interpolated missing Green

Fig-8:Interpolated missing Blue

The important demosaicking artifact we seek to identify is the false color artifact defined. As mentioned previously, false colors occur where there are abrupt changes in color, usually along an edge in the image. Using the constant color difference model G = R+k = B+j for k,j constant in a local neighborhood, the false coloring of an image is measured by divergence from this model by way of MSE. Given that false coloring occurs typically along edges, this method is only performed along edges.

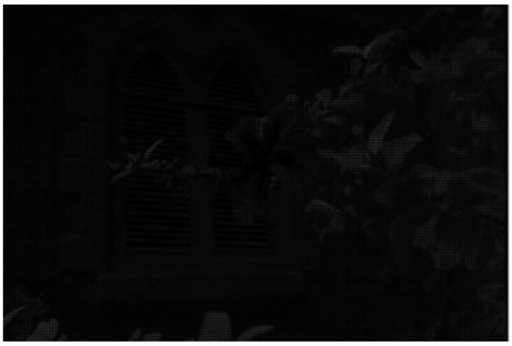

Fig-9:Color Difference

Color difference plane interpolation by logistic functional is the difference between directional variation. This approach is to derive a logistic functional to blend the diagonal and anti-diagonal estimation, leveraging the diagonal symmetry of the Bayer pattern. Then the green channel interpolation scheme is applicable to computing the rest missing values in the green-red and green-blue difference planes. The proposed demosaicking process is highly parallelizable: although the red and blue channels have to be estimated subsequently to the green channel estimation, the restoration in each step at a pixel is independent of the restoration of other pixels

Fig-10:Demosaicking image

CMSE and CPSNR are very simple techniques. Calculating CMSE involves first calculating the squared difference between the reference image and demosaiced image at each pixel and for each color channel. These are then summed and divided by three times the area of the image. CPSNR is then calculated using CMSE

$$CMSE = \frac{\sum_{i=R,G,B}\sum_{j=1}^{W}\sum_{k=1}^{H}(I_{i,j,k} - \overline{I_{i,j,k}})}{3WH}$$

$$CPSNR = 10log\left(\frac{255^2}{CMSE}\right)$$

where I is the reference image, I is the demosaiced image, and W and H represent the width and height of the image, respectively. Both of these methods fail to distinguish the case where the demosaiced image is only slightly different from the reference over many pixels from the case where the demosaiced image is vastly different from the reference image over few pixels. However, the second case represents an image with very severe artifacts, and thus a poorer quality image.

Image	PSNR	
	GD	Proposed
1	40.123	43.6384
2	40.0512	43.2424
3	38.2345	41.4331
4	25.9158	27.1951
5	27.3541	29.8313

4. CONCLUSIONS

This paper, proposed a very low cost edge sensing strategy, termed as LED.It guides the green channel interpolation and color difference plane interpolation by logistic functional of the difference between directional variation. Proposed system is highly parallelizable, and hence its easily restore very high resolution images in real time.Furthermore, in application scenarios where accuracy takes priority over speed.

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